Cognitively Adjusting Imprecise User Preferences for Service Selection

Lingyan Zhang, Shangguang Wang, *Senior Member, IEEE, Raymond K.Wong*, Fangchun Yang, and *Rong N. Chang, Senior Member, IEEE*

Abstract—Most state-of-the-art service selection approaches assume user preferences can be provided by the target user with sufficient precision and ignore historical service usage data for all users. It is desirable for ordinary users to possess a new service selection approach that can recommend satisfactory services to them even when their service selection preferences are specified imprecisely in terms of vagueness, inaccuracy, and incompleteness. This paper proposes a novel service selection approach that resolves the imprecise characteristics of user preferences and can recommend satisfactory services for users with varying cognitive levels in terms of service experience. The proposed service selection approach comprises of four major tasks: 1) employ user-friendly linguistic variables to collect apparent user preferences (AUP) and convert the linguistic variables to standardized fuzzy weights as AUP weights; 2) evaluate all users' respective cognitive levels for the target service type and obtain the cognitive level threshold for that type of services; 3) adjust the AUP weights based on the calculated cognitive levels and the threshold, and supplement the potential user preferences (PUP) weights; and 4) prioritize candidate services per a user satisfaction maximization objective. In-depth comparative experimental evaluations were performed using two real-world datasets. The results show that our service selection model outperforms three other representative ones and could provide a stable and reliable selection of services for the users with low service cognitive levels.

Index Terms—Service selection, QoS, user preferences, user cognitive level

I. Introduction

When there are many services that provide the same functional capabilities to users but differ in *quality-of-service* (QoS) properties, service selection becomes a QoS-driven decision problem in terms of user satisfaction maximization. QoS requirements for a user-specific service selection request are usually formulated as *user preferences*. Most state-of-the-art service selection approaches assume user preferences can be specified with sufficient precision, e.g., response time less than one minute.

However, in practice, user preferences for service selection are seldom specified well because the users often have limited service usage experience and service selection cognition [1]. It is desirable for the users to acquire a new service selection approach that can automatically select satisfactory services for them even when their service selection preferences are specified imprecisely in terms of vagueness [2], inaccuracy [1], and incompleteness [3].

Vague and inaccurate user preferences convey poorly actual user requirements. Moreover, user-specified service selection preferences often exclude good service selection criteria [4], [5], [6], [7] that could be learned from others' service usage experience and service selection preferences.

This paper proposes a novel service selection approach that considers the imprecise characteristics of user preferences and selects the most suitable services for users with varying cognitive levels in terms of service experience. We note that user preferences are used under many service selection models [3], [6], [10], [13], [43], [45], and are typically derived in four ways. First, the average of single-service, multi-users preferences [3] or multi-services, single-user preferences [4] is obtained based on users' service consumption context and history. Second, preferred weights or ranks of QoS attributes are consulted from users [6], [7], [10]. Third, comprehensive QoS languages [12], [13] are proposed to facilitate collecting user preferences. Fourth, linguistic terms and fuzzy logic [46], [47], [48] are used to capture user preferences to resolve vagueness and incompleteness issues. None of them take into account both the user preferences that are vague, inaccurate, and/or incomplete and the diversity of users' service consumption experiences and cognitive levels.

There are several service selection models [2], [6], [12], [43], [45], [47] that take into account imprecise characteristics of user preferences. The proposed fuzzy Linguistic preference models use linguistic terms and fuzzy logic [2], [6], [12], [47]; or use a fuzzy linguistic preference model [43] in which pair comparison between two QoS attributes is used; or use membership functions [45] to capture user preferences and use them to resolve preference vagueness and incompleteness. However, these models assign numeric weights with the same function, and they fail to consider the individual diversity of users in terms of user service experience and cognitive levels.

Our proposed service selection approach could adjust user preferences based on all users' respective cognitive levels. Realizing our service selection model consists of four phases. Firstly, we employ user-friendly linguistic variables [27], [28] to collect *apparent user preferences* (AUP),

• *L. Zhang, S. Wang, and F. Yang are with the State Key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunication，s,Xitucheng Road No. 10, Haidian, Beijing100876, China. E-mail: { zhanglingyan, sgwang, fcyang}*@bupt.edu.cn
• *Raymond K. Wong* is *with the School of Computer Science and Engineering, University of New South Wales, Austrilia. Email: wong@cse.unsw.edu.au*
• *Rong N. Chang is with IBM T.J. Watson Research Center, USA. Email: rong@us.ibm.com*

and obtain the AUP weights by converting the linguistic variables to standardized fuzzy weights. Secondly, we evaluate users' respective cognitive levels by applying information processing theory [29], [30], and obtain the threshold of cognitive levels (i.e., the baseline) by adopting the Otsu maximum class square error algorithm [31], [32]. Thirdly, we further adjust the AUP weights based on cognitive levels and the threshold, and supplement the *potential user preferences* (PUP) weights by employing the Rough set theory [33], [34]. Finally, the proposed approach (1) quantifies user preferences in fuzzy numbers to resolve vagueness, (2) returns the AUP weights and the PUP weights to resolve preference inaccuracy and incompleteness, and (3) prioritizes candidate services per a user satisfaction maximization objective.

The main contributions of this work are outlined below.

- First, we resolve the issues caused by vague, inaccurate, and/or incomplete user-specified service selection preferences. We could effectively adjust imprecise user preferences for service selection by taking into account both apparent and potential user preferences, and significantly improve service selection satisfaction and accuracy compared with other state-of-the-art approaches.
- Second, we create a user-dependent cognitive-level evaluation method as well as a user preference weight adjustment method (which uses cognitive-level values). The independent, portable, and expandable cognitive-level evaluation method can be exploited by the models that employ user preferences for service discovery, selection, and composition.
- Finally, we have conducted comprehensive experimental evaluations of our approach by employing two real-world datasets. QoS records of actual user service invocations and usage records are used in the experiments.

The remainder of this paper is organized as follows. Section II describes the motivation and challenges of this work. Section III discusses related research efforts. Section IV presents the proposed service selection approach. Section V shows the experimental evaluation results. Section VI concludes the paper and outlines future work.

II. Motivation and Challenges

In this section, we describe the motivation by giving an online service selection scenario, and analyze the challenges of delivering the desired service selection model, and finally we present the corresponding solutions.

II.A. Motivation

This section uses an online service selection scenario to exemplify the issues addressed by the proposed approach that cognitively adjusts imprecise user preferences for service selection. With reference to Fig. 1, Bob is a college freshman in India and would like to search for a good map-based location service for his college city via an online service selection tool. Due to his limited skills in composing service selection preferences and his weak service cognition, he uses the tool to search for the location services that are highly reliable. Via a service registry located in the United States, the tool recommends him use Service A, which has the highest reliability property. Bob tries the service hosted in Canada. He then realizes that response time for service execution is more important for his continued use of the location service. Being dissatisfied with the selection, he submits a service selection request to the tool with his new preferences. He becomes satisfied with the new selection: Service K, which is hosted by a local company and was ranked lower earlier in terms of reliability (e.g., returning "internal server error" messages from time to time).

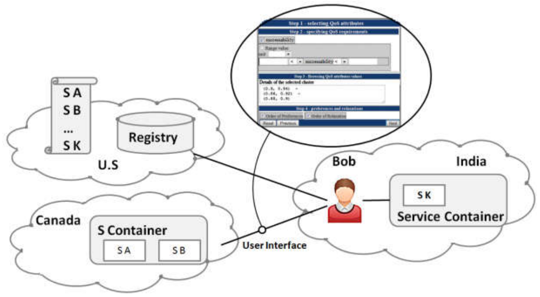

Fig. 1. The motivating scenario.

The scenario shows that it is desirable for many users like Bob to be able to receive satisfactory services selections effectively and efficiently via imprecise personal preferences. To the best of our knowledge, most of service selection models [4], [7], [10], [17], [20], [43], [45] assume the availability of accurate user preference specifications and do not target at inexperienced service users like Bob. Although some of them note the importance of user preferences [1], [3], [6], [8], they make insufficient attempts to analyze imprecise user preferences and end up with a user interface design that is too complicated and technical for ordinary users. Moreover, feeding their service ranking mechanism with unexpected type of user preferences makes their solutions unable to effectively compute comprehensive QoS properties for the users.

II.B. Challenges and Solution Summary

Delivering the desired service selection model must attack several nontrivial challenges: 1) How to model the user preferences for service selection so that ordinary users can intuitively express preferences? 2) How to evaluate and automatically improve the preciseness of user preferences? 3) How to recommend satisfactory services with no need for the users to provide precise user preferences?

The first challenge requires enabling the users to express how they value every QoS attribute for a specific service selection using common words and/or phrases (instead of numbers or special purpose languages). It also excludes the option of gathering precise user preferences via a complicated and/or technical user interface. It essentially requires us to be able to resolve the three user preference specification issues listed below:

- **Vagueness** [2]: When the user preference over a specific QoS attribute is difficult to quantify precisely, it becomes nontrivial to decide on an appropriate weight for the attribute.
- **Inaccuracy** [1]: The aforementioned motivating scenario shows that an inexperienced user with no

cognition about what the realistic QoS values are may pick 100% availability as the only preference for selecting a responsive service that is available 24x7. The candidate services cannot be ranked satisfactorily for the user due to the user-provided incorrect user preference specification.

- **Incompleteness** [3]: The motivating scenario also shows that user satisfaction with the selected service could be impacted negatively when some important QoS attribute is not specified, which could be caused by the user's lack of service usage experience.

In light of these characteristics of imprecise user preferences, we introduce two types of user preferences: *apparent user preference* (AUP) and *potential user preference* (PUP). AUP is collected directly from the users (which could be done via questionnaires, interviews, and/or open-ended questions). The accuracy of AUP for a service selection request varies depending on users' service experience and cognitive levels. PUP is a set of potential preferences for the QoS attributes extracted from all users' service usage history, and can be used to supplement AUP for a service selection request. Availability of subjective AUP and extracted PUP enables us to adjust user-provided service selection preferences with the goal of recommending satisfactory services to the requesting user in terms of service functionalities and QoS properties.

More specifically, our proposed solution includes a user-friendly means of flexibly expressing QoS preferences and measuring the reliability of user preferences in terms of users' cognitive levels. We have created a weight-adjusting algorithm for the solution in terms AUP and PUP such that, under the proposed service selection model, user preferences can be adjusted effectively and automatically based on user cognitive levels.

III. Related Work

Many QoS-based service selection approaches have proposed in recent years [38], [39], [40], [41], [42], [44]. In terms of the focus of this paper, we review only the service selection models that consider user preferences [4], [7], [10], [17], [20], [46], [47], [48]. The reviewed models are classified into four categories.

Models in the first category [3], [4] consider only universal user preferences rather than request-specific preferences of the target user. Wang, Lee and Ho [3] take the average of single-service, multi-users preferences as the preference of the target user. Kang et al. [4] extract user preferences from users' service usage history and average the preferences of multiple employed services as the user preference. These models are easy to implement and can easily obtain the user preference value. However, universal preference-based models ignore the individual differences in preferences among the users and services. For example, different users may have different preferences regarding the same service, while differences may also exist in users' preferences for different services.

The second category of models [6], [7], [8], [9], [10], [11] emphasizes self-reported preferences (i.e., the AUP) and adopts the preferred weights or ranks of QoS attributes from users. Zeng et al. [7] propose a local selection approach to maximizing preferences while satisfying imposed constraints. Li, Su, and Chen [8] introduce QoS attribute sorting and weights for service selection. They provide an order relation vector to present the QoS order of user preferences. Zhao et al. [6] propose a fuzzy ranking method to adjust preferences by analyzing user choices. We note that the method requires submission six times to capture the preference value, and the improvement may not be good because preferences for dissimilar services can significantly vary. In general, users of this type of models are expected to formulate QoS preferences, ranks, and/or weights precisely, and some of these methods end up with overly complex service user inputs.

In the third category, multiple comprehensive QoS languages [1], [14], [15], [17] and standardized representations [12] are proposed to collect relatively more accurate user preferences. Users may need to have knowledge on ontology [14], utility function [16], or QoS query language [17]. Lamparter et al. [13] propose a formal standards-based representation for dynamic user preferences based on the current user context. We note that most service users may not have the required expertise or skills, or they may not offer all the input required by the selection models. Without proper input, the selection model cannot generate satisfying results, no matter how well-designed the algorithm is.

Service selection models in the fourth category adopt fuzzy Linguistic preference models [43], [45]. Almulla, Almatori, and Yahyaoui [2] propose a method for personalized preference-based service selection using fuzzy logic. Zhao et al. [43] proposes a fuzzy linguistic preference model in which pair comparison between two QoS attributes is used in terms of four levels of preference intensities. Modekurthy, Fletcher, and Liu [45] propose a fuzzy logic model to capture user's preference by a membership function. Fletcher et al. [47] propose a method for user preferences-based service selection using linguistic terms and fuzzy logic, which resolves vagueness and incompleteness. We note that these models [2], [43], [45], [47] assign numeric weights with the same function, and they fail to consider the individual diversity of users in terms of user service experience and cognitive levels.

Fuzzy preference processing has been studied in traditional decision making problems [18], [19], [20], [49]. The decision makers (experts) in these models or methods [18], [19], [20], [21] are usually composed of diverse specialists. Paired comparison methods are commonly used to capture expert preference information. They are not suitable for the circumstance of service selection among numerous candidates, because common users usually do not possess precise knowledge or a sufficient level of it; consequently, they are unable to give the pair wise comparison weights on the numerous service candidates.

In short, inexperienced service users are not the main focus of previous QoS-based service selection models [4], [7], [10], [17], [20], [43], [45]. Moreover, some of these models assume users to be sufficiently experienced to input exact and accurate preference information, and some of these methods end up with overly complex service user inputs, and the individual diversity of users in terms of their service experience and cognitive levels is ignored. In reality, service users could be inexperienced, slightly experienced, and highly experienced. Therefore, an ideal service selection model should consider all these kinds of users. The proposed service selection approach provides a better service selection model for all kinds of users, and employs a novel user preference adjustment algorithm with consideration of user cognitive levels.

IV. Service Selection Model

This section presents an optimization model for the aforementioned service selection problem, whereby the service user gives a fuzzy expression for each of the preferred QoS properties (which could be affected by time pressure, limited service usage experience, and/or low service cognitive level). The proposed service selection model is built in a four-step process: user preference quantification (Section IV.A), cognitive level and threshold calculation (Section IV.B), user preference adjustment (Section IV.C), and service selection (Section IV.D). Table I lists the symbols that will be used in the rest of this paper.

TABLE I
MAJOR SYMBOLS AND DESCRIPTIONS

Symbols	Description
a_i	The i^{th} QoS attributes
K	The number of QoS attributes
M	The number of service candidates
q_{ij}	The j^{th} QoS attribute value of the i^{th} service
nq_{ij}	The normalized value of q_{ij}
Q	The QoS matrix of M services and K attributes
Q'	The normalized matrix of Q
L_i	The cognitive level of the i^{th} user
L_{target}	The cognitive level of the target user
G	The number of historical users, i.e., #users
CL	The set of G users' cognitive levels
$L_{\min}$	The min value of CL
$L_{\max}$	The max value of CL
$L_{threshold}$	The threshold of users' cognitive level
W_i	The original AUP weight of QoS attribute a_i
AW_i	The adjusted AUP weight of QoS attribute a_i
PW_i	The PUP weight of QoS attribute a_i
IW_i	The integrated weight of QoS attribute a_i
ρ_1, ρ_2	The adjustment coefficients of W_i
α	The preference coefficient of AW_i

IV.A. User Preference Quantification

Establishing the selection vector for each user requires each user to express her/his service selection preferences with respect to each QoS attribute, which is hereby designated as the AUP. This can be performed, e.g., by self-reported questionnaires (which solicit user input for the preference weight of each QoS attribute). In the user-specific weight vector $W = \{W_1, W_2, \ldots, W_K\}$, where K is the number of QoS attributes, the value of parameter W_i reflects how highly the user values the corresponding QoS attribute a_i .

A general-purpose service selection model should provide an easy, user-friendly, and flexible way for ordinary users to express their service selection preferences [1]. This section will explain how the proposed approach captures QoS preference weights via linguistic variables, whose values are common words or phrases, not numbers. These linguistic variables are converted to standardized fuzzy numbers per the conversion scale in use.

IV.A.1. Linguistic Variables Collection

Comprehensive QoS weights should be aggregated and computed per user preferences. However, user preferences usually vary in form and depth. A user may not indicate their preferences at all, or may represent preferences in the form of attributes or alternatives [6], [8]. Many studies have been conducted on fuzzy preference problems [2], [24], [25], [26], [49], [50]. A particularly active research topic is the employment of the fuzzy set theory when imprecise information is represented in fuzzy terms.

It is difficult for conventional quantification to express well the estimated values of AUP because user-provided preferences are usually subjective and vague. Thus, linguistic variables, as defined earlier, are used. Without loss of generality, qualitative AUP of QoS attributes are currently evaluated by each service user in terms of five linguistic variables (namely, "absolutely important," "strongly important," "essentially important," "weakly important," and "little important") with respect to the fuzzy five-level scale [27], [28], shown in Table II.

IV.A.2. Standardized Fuzzy Number Conversion

The AUP of QoS attributes are evaluated for each user in terms of linguistic variables; thus, the variables must first be transformed into fuzzy numbers by an appropriate conversion scale. The principle of this step is to select a scale that matches all the linguistic variables and to employ fuzzy numbers on that scale to represent the meaning of these linguistic terms.

In the proposed method, a numerical approximation model [27], [28] is used to systematically convert linguistic variables to their corresponding fuzzy numbers. We employ the triangular fuzzy numbers to express the fuzzy weights, as showed in Table II. Let $W_i = (l_i, m_i, u_i)$ be a triangular fuzzy number with median m_i , low boundary l_i and upper boundary u_i ; and represent the AUP weight with respect to QoS attribute a_i .The linguistic variables are converted to fuzzy numbers using the conversion scale shown in Table II. We set the maximum of "absolutely important (AI)" is 0.9 rather than 1. The goal is to make room for AUP weight adjustment. Moreover, the weight numbers of all QoS attributes would be normalized, ranging from 0 to 1. These area ([0,0.1] or [0.9,1]) would be included.

The conversion method is easy to understand and use for ordinary users. When the set of AUP linguistic variables need be extended to support non-standard ones (e.g., "approximately equal to ten") and result in non-standard fuzzy numbers, all of the existing fuzzy numbers must be converted per a standardization process. Assuming that a positive triangular fuzzy number $W_i = (l_i, m_i, u_i)$ is used to represent the estimated preference for QoS attribute a_i , where $0 \le l_i \le m_i \le u_i \le c$ and c is the maximum value of non-standardized triangular fuzzy numbers selected by the user for QoS attribute a_i . We translate each triangular

TABLE II
LINGUISTIC VARIABLES AND FUZZY WEIGHTS

Linguistic Variables	Triangular Fuzzy Weights
Little important (LI)	(0.1, 0.1, 0.3)
Weakly important (WI)	(0.1, 0.3, 0.5)
Essentially important (EI)	(0.3, 0.5, 0.7)
Strongly important (SI)	(0.5, 0.7, 0.9)
Absolutely important (AI)	(0.7, 0.9, 0.9)

fuzzy number $W_i = (l_i, m_i, u_i)$ given to QoS attribute a_i into a standardized triangular fuzzy number $W_i^*(i = 1,2,...,K)$, where

$$W_i^* = (l_i / c, m_i / c, u_i / c) = (l_i^*, m_i^*, u_i^*) \quad (1)$$

$0 \le l_i^* \le m_i^* \le u_i^* \le 1$ and K is the number of QoS attributes.

IV.B. Cognitive Level and Threshold Calculation

Information processing [29] is defined as the conversion of latent information into manifest information. The process of expressing personal preferences for a specific service type *after* using one of more instances of it essentially converts latent information (service experience) into manifest information (QoS cognition), which conforms to the principle of information processing theory. In this section, we propose a method for calculating the cognitive level threshold for each service type based on information processing theory, which is necessary to measure the reliability of the AUP weights.

IV.B.1. Cognitive Level Calculation

The goal of information processing is to understand human thinking in relation to how they process, recollect, and express historical experience. Craik [30] proposes that deeper processing is correlated with higher levels of subsequent remembering and recollected experience. The accuracy and completeness of recollected experience depend on the processing depth, and the processing time serves as an index of depth. Different users would have different understandings and cognitive levels for the same service type due to their different experiences with services of the same type. These factors affect the accuracy and completeness of user-provided preferences. For example, the preferences of a user for a specific service type would not be useful in selecting satisfactory services if the user has never consumed any services of that type.

In general, information guidance (i.e., the accuracy and completeness of the user preference expression) relates to the user's cognitive level in terms of service experience. Per the processing theory, the ability to deliver a clear, precise, and appropriate expression of material depends on the depth of processing the input material.

Since the depth of user processing of the service materials relates to the processing time and frequency, longer time and a higher frequency of a user employing services of the same type, higher is the user's cognitive level for the service type (and smaller is usage interval, deeper is processing). In other words, the cognitive level of the user to the requested service is positively correlated with the total time and total number of uses of the same type of service, and is negatively correlated with the total usage interval. Let L_i denote the cognitive level of the i^{th} user to the requested service, and the value of L_i is calculated as follows:

$$L_i = \begin{cases} \dfrac{< number\,of\,times > \bullet < usage\ time >}{< \mathrm{int}val\ time >} = \dfrac{n \bullet \sum_{t=1}^{n} st_t}{\sum_{t=1}^{n-1} si_t + si_0}, if\ n > 0 \\ 0, if\ n = 0 \end{cases}, \quad (2)$$

where n is the number of times the user employs the services of the same type, st_t is the duration of the t^{th} use of the service, si_t is the interval between the t^{th} use and the $(t+1)^{th}$ use, and si_0 is the time since the last use of the service. It shows clearly how a user's cognitive level for a specific type of services is computed in terms of the user's usage history for that type of services.

IV.B.2. Threshold of Cognitive Level per Service Type

We note that one service-type-specific cognitive level for a specific user cannot serve as an absolute index of depth across different types of services nor across different users. Thus, we must determine one user-independent cognitive level threshold for each type of services to facilitate effective adjustment of user-provided service selection preferences (e.g., when other users' preferences can be used to improve the requesting user's service selection preferences).

Every cognitive level threshold classifies the users into two groups with respect to the target service type: *semantic level users* and non-semantic level users. Semantic level users can make better association between QoS attribute values and real service experience for the target service type than the non-semantic ones. Ideally the threshold can maximize the separability between the two classes of users. To be able to automatically compute such ideal thresholds, the Otsu maximum class square error method [31], [32] is used. The method effectively calculates the threshold that maximizes the between-class variance.

Supposing we have obtained the set of users' cognitive levels, CL, for the target service type using the cognitive level calculation method. Let cognitive levels of all users be represented in L levels, $[1,2,...,L]$. The number of users at level i is denoted by n_i and the total number of users by $N = n_1 + n_2 + ... + n_L$. To simplify the discussion, the cognitive-level histogram is normalized and regarded as a probability distribution as follows:

$$p_i = n_i / N, \quad p_i \ge 0, \sum_{i=1}^{L} p_i = 1. \quad (3)$$

Now, suppose that we dichotomize cognitive levels of users into two classes — C_0 and C_1 (the non-semantic and semantic cognitive level) — by a threshold at level k. C_0 denotes cognition with levels $[1,...,k]$, and C_1 denotes cognition with levels $[k+1,...,L]$. Then, probabilities of the class occurrence and class mean levels, respectively, are given by the following formulas:

$$\omega_0 = \sum_{i=1}^{k} p_i = \sum_{i=1}^{k} n_i / N, \quad (4)$$

$$\omega_1 = \sum_{i=k+1}^{L} p_i = \sum_{i=k+1}^{L} n_i / N = 1\text{-}\omega_0, \quad (5)$$

with

$$\mu_0 = \sum_{i=1}^{k} ip_i / \omega_0, \quad (6)$$

TABLE III
EXAMPLE OF AN INFORMATION TABLE

A \ U	Response Time(R)	Through-put(T)	Availabil-ity(A)	Cognitive Level
u_1	WI	WI	LI	*High*
u_2	EI	WI	LI	*Low*
u_3	EI	WI	LI	*High*
u_4	LI	LI	LI	*Low*
u_5	EI	LI	WI	*Low*
u_6	HI	LI	WI	*High*

$$\mu_1 = \sum_{i=k+1}^{L} ip_i / \omega_1, \quad (7)$$

$$\mu = \sum_{i=1}^{L} ip_i. \quad (8)$$

The between-class variance is evaluated as follows:

$$\delta^2(k) = \omega_0(\mu-\mu_0)^2 + \omega_1(\mu-\mu_1)^2. \quad (9)$$

Otsu uses the measuring function below to obtain the threshold $\hat{k}$ (which separates the two classes with the maximum between-class variance):

$$L_{threashold} = \delta^2(\hat{k}) = \arg\max_{1\le k\le L}(\omega_0(\mu-\mu_0)^2 + \omega_1(\mu-\mu_1)^2). \quad (10)$$

Thus, we obtain the threshold of users' cognitive levels, $L_{threashold}$, which is regarded as a baseline for dividing the semantic cognitive level and non-semantic cognitive level.

IV.C. User Preference Adjustment

After fuzzy numbers of user preferences and cognitive levels of users (for the target service type) are obtained, all QoS weight assignments are ready to be adjusted. The user preference adjustment is done via a two-step process: modifying the AUP weights, and discovering PUP weights. The process resolves inaccuracy and incompleteness of user-provided preferences. Being able to adjust the weights of user-provided preferences based on the cognitive levels of all users is the key to the superiority of the proposed service selection approach.

IV.C.1. AUP Weights Adjustment

This section presents how we adjust the AUP weights based on users' cognitive levels to strengthen or weaken the influence of AUP for the service selection decision.

Section IV.A shows how we obtain the fuzzy AUP weight for the target user with respect to QoS attribute a_i, $W_i=(l_i,m_i,u_i)$. Section IV.B describes how we obtain the target user's cognitive level, L_{target}, the threshold level, $L_{threashold}$, and the maximum and minimum values of all users' cognitive levels, indicated as $L_{\min}$ and $L_{\max}$, respectively. For the triangular fuzzy number, $W_i=(l_i,m_i,u_i)$, we calculate the adjusted AUP weight to remove fuzziness. The adjustment formula for the AUP weight with respect to QoS attribute a_i, AW_i, is defined as follows:

$$AW_i = \begin{cases} \dfrac{(\rho_1 \times L_{target} - L_{threshold}) \times (u_i - m_i)}{\rho_1 \times L_{\max} - L_{threshold}} + m_i, \ if\ L_{target} > L_{threshold} \\ m_i, \quad if\ L_{target} = L_{threshold} \\ m_i - \dfrac{(\rho_2 \times L_{target} - L_{\min}) \times (m_i - l_i)}{\rho_2 \times L_{threshold} - L_{\min}}, \ if\ 0 < L_{target} < L_{threshold} \\ l_i, \quad if\ L_{target} = 0 \end{cases}, \quad (11)$$

where AW_i is the adjusted AUP weight of QoS attribute a_i, and ρ_1 and ρ_2 are the adjustment factors for strengthening and weakening the influence of the AUP weight, respectively. ρ_1 and ρ_2 are in the range of $[1,+\infty)$.

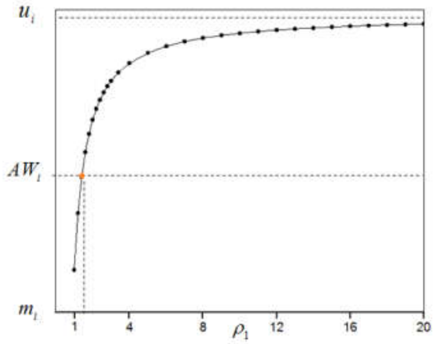

Fig. 2. The impact of ρ_1 onthe AUP weight, AW_i.

When the cognitive level of the target user is above the threshold, the value of AW_i is between the median, m_i, and the upper boundary, u_i; otherwise, it is between the lower boundary, l_i and the median, m_i. A high value of ρ_1 or ρ_2 indicates a higher level of adjustment. The impact of ρ_1 on the AUP weight is shown in Fig. 2. The impact of ρ_2 on the AUP weight follows the similar pattern when the user's cognitive level is below the threshold.

IV.C.2. PUP Weights Extraction

This section presents, for a specific service type, how we discover the PUP (Potential User Preferences) and determine the PUP weights (of the service type's QoS attributes). The PUP is extracted based on the service type's historical preference data correlated with *all users*' cognitive levels. The PUP-extraction process is achieved by applying the Rough set theory [33], [34].

The Rough set theory is a technique for addressing uncertainly in knowledge discovery. A fundamental principle of a Rough set based model is to discover redundancies and dependencies between the given features of a problem to be classified. Thus, the Rough set theory could be used to effectively discover the non-redundant PUP attributes among multiple QoS attributes, and compute the PUP weights in terms of the relationship between all users' preferences and all users' cognitive levels. The procedure is summarized below:

Step 1. Information table $I=(U,P)$ creation.

Let:

- U be a set of N users who consumed the same type of services in the past, $U=\{u_1,u_2,...,u_N\}$, $N\ge 1$;
- C be a set of K conditional attributes that describe all users' preferences on K QoS attributes in terms of their past consumption experience with the target service type, $C=\{c_1,c_2,...,c_K\}$, $K\ge 1$;
- D be a set of the decision attributes that describe user cognitive levels to the target service type, $D=\{d_1\}$;
- P be a set of $K+1$ properties that describe the N users of set U, $P=C\cup D$;
- $a(x)$ be the value of attribute $a(a\in P)$ for user

TABLE IV
(C, D) -DISCERNIBILITY MATRIX FOR TABLE II

	u_1	u_2	u_3	u_4	u_5	u_6
u_1		*R*	-	*R,T*	*R,T,A,*	-
u_2			$\varnothing$	*R,T*	-	*R,T*
u_3				*R,T*	*T,A*	-
u_4					-	*R,*
u_5						*I*
u_6						

$x(x \in U)$.

Per the Rough set theory, we have information table $I=(U,P)$.

We depict the above concept by means of a simple example. When computing the PUP weights of the QoS attributes for the target service type desired by Bob, we begin with an example information table as shown in Table III. The table contains data for six users who consumed the same type of service in the past. In the table, $\{\mathrm{Re}\,sponseTime(R), Throughput(T), Availability(A)\}$ is a set of condition attributes, which conveys all users' preferences on three different QoS attributes, whereas $\{CognitionLevel\}$ is the decision attribute set that reveals all users' cognitive levels to the target service type.

In the information table, some attributes are more important than others for characterizing the relationship between conditional attributes, C, and decision attributes, D. For example, ResponseTime may be more important than Availability as we discuss later in Step 2. Thus, in the next step, we obtain the subset of attributes that can fully characterize the relationship in the information table. Such an attribute set is called D-reduct P_A, where $P_A \subseteq C$.

Step 2. D-reduct P_A calculation.

Let:

- U, C, D, and I be defined in Step 1;
- I_D be an indiscernibility relation determined by D and is defined as follows:
  $$I_D = \{(x,y) \in U \times U \mid a(x)=a(y), \forall a \in D\}\,; \tag{12}$$
- $[x]_D$ be an equivalence class of users that are exclusively defined by the attributes of set D, $x \in U$;
- L/I_D be a set of all equivalence classes partitioned by I_D, $L/I_D = \{[x]_D \mid x \in U\} = \{X_1, X_2, ..., X_n\}$;
- P_A be the set of H attributes that discern any two users of U that do not belong to the same equivalence class of relation I_D; i.e., $\forall x, y \in U, (x,y) \notin I_D$, $P_A = \{p_{A1}, p_{A2}, ..., p_{AH}\}$, $P_A \subseteq C$.

To compute the D-reduct of condition attributes, C , we need a slightly modified discernibility matrix called the (C,D)-discernibility matrix, which is given as follows:

$$\delta(x,y) = \{c_k \in C : c_k(x) \neq c_k(y) \; and \; (x,y) \notin I_D\}. \tag{13}$$

Each (C,D)-discernibility matrix uniquely defines a discernibility (Boolean) function $f_D(C)$, which is defined as follows:

Algorithm1. *D*-reduct Computation

```
Input: information table I = (U, P) , the indiscernibility relation I_D
Output: D-reduct P_A
Create the (C, D) -discernible matrix M for table I
M ← [N][N]
for i ← 1 to N
    for j ← 1 to i
        M[i][j] ← ∅
        for k ← 1 to K
            if (u_i, u_j) ∉ I_D and c_k(u_i) ≠ c_k(u_j) then
                if M[i][j] = ∅ then
                    M[i][j] ← c_k
                else
                    M[i][j] ← BooleanAddition(M[i][j], c_k)
                end if
            end if
        end for
        if M[i][j] ≠ ∅ then
            f_D(C) ← BooleanMultiplication(M[i][j], f_D(C))
    end for
end for
P_A ← the first constituent in the minimal disjunctive normal f_D(C)
return P_A
```

$$f_D(C) = \prod_{(x,y)\in U} \{\textstyle\sum \delta(x,y) : (x,y) \in U^2 \; and \; \delta(x,y) \neq \varnothing\}, \tag{14}$$

where each attribute $c_k (c_k \in C)$ is assigned to a binary Boolean variable, and $\sum \delta(x,y)$ is the Boolean sum of all Boolean variables assigned to the set of attributes $\delta(x,y)$. The first constituent in the minimal disjunctive normal form of the function $f_D(C)$ is taken as P_A. This process is illuminated in Algorithm 1.

We depict the above concept by means of a simple example. Given Table III, we can obtain the sets of equivalence classes, $U/I_D = \{\{u_1,u_3,u_6\},\{u_2,u_4,u_5\}\}$. The (C,D)-discernibility matrix for Table III with condition attributes R , T , A and decision attribute $CognitionLevel$ is given in Table IV. In addition, $f_D(C) = R \cdot (T+A)$, where "+" and " • " denote Boolean addition and multiplication, respectively. We note that T and A are equally important in characterizing the relationship in the information table. In this case, both $\{R,T\}$ and $\{R,A\}$ are D-reducts, and their contributions to the result of our model are the same. Thus, we just choose $\{R,T\}$ as the D-reduct in the following example.

Step 3. Significance of attributes of P_A calculation.

It follows from considerations of D-reduct of C , P_A, that no two attributes of P_A can have equal importance. The idea of attribute significance can be generalized by introducing a concept of significance of attributes, which enables us to evaluate attributes by assigning to an attribute a real number from the closed interval [0,1], thereby expressing how important an attribute is in an information table.

The set of all users can be uniquely classified in blocks of the partition by the information table. The significance of an attribute in the information table can be evaluated by measuring the change in user classification ability of the information table after removing the attribute.

Let:

- U , C , D , and I be defined in Step 1, P_A and L/I_D be defined in Step2;
- P'_A be a subset of P_A , $P'_A(P'_A \subseteq P_A)$;
- $\underline{P'_A}(L/I_D)$ be the lower approximation of the set L/I_D that is defined as follows:

$$\underline{P'_A}(L/I_D)=\{x\in U:[x]_{P'_A}\subseteq L/I_D\}, \tag{15}$$

- $POS_{P'_A}(D)$ be the positive region of the portion U/I_D with respect to P'_A and be the set of all users of U that can be uniquely classified in blocks of the partition U/I_D by means of $P'_A(P'_A \subseteq P_A)$, which is defined as follows:

$$POS_{P'_A}(D)=\bigcup_{X\in U/I_D}|\underline{P'_A}(L/I_D)|, \tag{16}$$

- $\gamma(P'_A,D)$ be the dependency number that expresses the degree of dependency between $P'_A(P'_A \subseteq P_A)$ and D , defined as follows:

$$\gamma(P'_A,D)=\frac{|POS_{P'_A}(D)|}{|U|}=\sum_{X\in U/I_D}\frac{|\underline{P'_A}(L/I_D)|}{|U|}, \tag{17}$$

- σ_{P_AD} be the set of H significances of attributes of P_A, $\sigma_{P_AD}=\{\sigma_1,\sigma_2,...,\sigma_H\}$.

For each attribute $p_{Ai}(p_{Ai}\in P_A)$, we normalize the difference and define the significance of p_{Ai} as follows:

$$\sigma_{P_AD}(p_{Ai})=\frac{(\gamma(P_A,D)-\gamma(P_A-\{p_{Ai}\},D))}{\gamma(P_A,D)}, \tag{18}$$

$$\sigma_{P_AD}(p_{Ai})=1-\frac{\sum_{X\in U/I_D}|\underline{P_A-\{p_{Ai}\}}(X)|}{\sum_{X\in U/I_D}|\underline{P_A}(X)|}. \tag{19}$$

The value of $\sigma_{P_AD}(a)$ is between 0 and 1. The greater the significance value is, the more important the attribute is among all attributes.

We depict the above idea using a simple example. Given Table III, we obtain $P_A=\{R,T\}$ in Step 2. For the two attributes of P_A, R and T , we can obtain the attribute significance $\sigma_{P_AD}(R)$ and $\sigma_{P_AD}(T)$ according to (18) and (19).

Step 4. The PUP weights calculation.

After obtaining the significance of each attribute, p_{Ai} $(p_{Ai}\in P_A)$, we can calculate the PUP weight with respect to QoS attribute c_i $(c_i \in C)$. As shown in Lines 5-11 of Algorithm 2, if $c_i \in P_A$, PW_i is computed as follows:

$$PW_i=\sigma_{P_AD}(c_i)/\sum_{i=1}^{H}\sigma_i, \tag{20}$$

otherwise, PW_i=0 . Thus, we obtain the PUP weights based on the corresponding preference data correlated with *all users*' cognitive levels. For example, in Table III, we can obtain the set of PUP weights on three attributes, i.e., R, T, and A, respectively, per (20).

Algorithm2. PUP weights calculation

Input: D-reduct P_A ,the set of attributes significance σ_{P_AD}
Output: the set of PUP weight PW

```
1.  SigSum ← 0 , j ← 1
2.  for i ← 1 to H
3.      SigSum+ = σ_i
4.  end for
5.  j ← 1
6.  for i ← 1 to K
7.      if c_i ∈ P_A then
8.          PW[i] ← σ_j / SigSum , j+ = 1
9.      else PW[i] ← 0
10.     end if
11. end for
12. return PW
```

IV.D. Service Selection

In this section, we first obtain the normalized QoS matrix Q per K QoS attributes by setting a threshold regarding the qualities and using a Gaussian normalization method [10], [35], [36]. We then use weighted summation of the AUP weights and the PUP weights to obtain the integrated QoS weights. Finally, the overall score of each candidate service is uniformly calculated by summing the product of each normalized attribute value and its corresponding weight. The service with the highest score is the selected service.

IV.D.1. QoS Matrix Normalization

The objective of the service selection model is to select satisfying services for users. By setting a threshold regarding the service qualities, we can obtain a set of M $(M>1)$ service candidates of the same functionality, S $(S=\{s_1,s_2,...,s_M\})$. We can then obtain the following matrix Q according to K QoS attributes:

$$Q=\begin{pmatrix} q_{1,1} & q_{1,2} & \cdots & q_{1,K} \\ q_{2,1} & q_{2,2} & \cdots & q_{2,K} \\ \vdots & \vdots & \ddots & \vdots \\ q_{M,1} & q_{M,2} & \cdots & q_{M,K} \end{pmatrix}, \tag{21}$$

where each row represents a service, s_i , while each column represents one of the QoS attributes.

To rank the candidate services, the QoS matrix Q must be normalized. The purpose of normalization is to enable a uniform measurement of service qualities independent of the quality units in use. There are many QoS matrix normalization approaches, such as linear conversion, logarithmic conversion, and Gaussian conversion [10], [35], [36]. The advantage of the Gaussian conversion process over typical linear conversion is that the presence of a few abnormally large or small values does not bias the importance of any attribute element when computing the overall scores of services.

In this paper, we employ the Gaussian conversion to normalize the QoS matrix, as shown in (22). Each element in matrix Q is normalized using the following equation:

$$nq_{i,j}=\frac{q_{i,j}-\overline{q_{i,j}}}{\varphi_1\times 3\sigma_j}+\varphi_2, \tag{22}$$

where $\overline{q_{i,j}}$ is the mean of values on QoS attribute a_j in matrix Q and σ_j is the standard deviation. We use $3\sigma_j$

per the $3-\sigma$ rule, which helps to normalize the value into the range of [-1,1]. The probability of the normalized value being in the range of [-1,1] is approximately 99% [35]. In practice, we set $\varphi_1 = 2$, $\varphi_2 = 0.5$, and ensure all the attribute element values are within the range of [0,1] by mapping every out-of-range value to either 0 or 1.

Applying equation (22) to Q, we obtain the normalized matrix Q', which is shown below:

$$Q' = \begin{pmatrix} nq_{1,1} & nq_{1,2} & \cdots & nq_{1,K} \\ nq_{2,1} & nq_{2,2} & \cdots & nq_{2,K} \\ \vdots & \vdots & \ddots & \vdots \\ nq_{M,1} & nq_{M,2} & \cdots & nq_{M,K} \end{pmatrix}. \tag{23}$$

IV.D.2. Calculation of Integrated QoS Weights

Section IV.C describes how we calculate the AUP weights and the PUP weights. In this section, the comprehensive weights in favor of correct estimations and decisions are obtained by integrating the AUP weights with the PUP weights. The integration weight, IW_i, of QoS attribute a_i is calculated as follows:

$$IW_i = \alpha \cdot AW_i + (1-\alpha) \cdot PW_i, \tag{24}$$

where α is a preference coefficient that denotes the trust level to the AUP, and α is in the range of $[0,1]$. When $\alpha = 1$, only AUP is considered.

IV.D.3. Overall Quality Score Calculation

The QoS performance of each qualified service $s_i (1 \le i \le M)$ can be uniformly calculated by summing the product of each normalized attribute value and its corresponding weight, as shown below:

$$Score(s_i) = \sum_{j=1}^{K} (nq_{i,j} * IW_j), \tag{25}$$

where $nq_{i,j}$ is the normalized value of service s_i with respect to QoS attribute a_j; and IW_j is the integration weight of QoS attribute a_j. The attributes are assumed to be independent of each other.

For a given service selection request, the model chooses the service that satisfies all of the user constraints and that has the maximal score. The service with the highest score is selected as the final service $s (s \in S)$ as follows:

$$Score(s) = \max_{1 \le i \le M} \{\sum_{j=1}^{K} (nq_{i,j} * IW_j)\}, \tag{26}$$

where M is the total number of service candidates, and K is the number of QoS attributes.

V. Experimental Evaluations

In this section, we present an in-depth comparative performance evaluation of the proposed service selection approach. We adopted two real-world datasets as part of the experiment setup (Section V.A), compared our approach with several previous approaches [5], [11], [37], [6], [12] (Section V.B), and analyzed the parameter impact on the selection results (Sections V.C and V.D). This section concludes with a discussion on the insights we obtained through the experiments (Section V.E).

V.A. Experiment Setup

The QWS dataset[1] [41], [42] is included as part of our experiment setup. That is a real-world web service QoS performance dataset containing 2,507K records. Most of the Web services were accessible through the public Internet. Every record in the dataset is associated with a Web service. There are nine QoS attributes, four of which are selected for this work: response time, throughput, availability, and latency. The QoS preference records and service usage records are collected from half of a million users by CNNIC[2]. We picked up the usage records of web browsing in the CNNIC dataset and make it relevant to the same type of services in the QWS dataset. And we randomly extracted 11.2 million QoS preference records and obtained 1,000 users with service usage levels ranging from complete novice to expert.

We divided the 1,000 users into two groups: historical users and active users. To simulate the real-world situation in which users have varying cognitive levels, we randomly removed a certain number of historical users with their service usage records. We also removed some active users that have many usage records because a real user normally consumes a small number of services.

To evaluate the selection performance, we compare our approach with the user-based additive weighting (AW) method [5], [11], [36], [37], fuzzy ranking (FR) method [6], and fuzzy logic (FL) method [12]:

- **AW** is a user-preference-based additive weighting method that expresses the overall quality score of each candidate service. The overall quality score is the weighted sum of the QoS attribute values and the preference weights assigned by the user.
- **FR** is a fuzzy ranking method that sorts all the solutions based on QoS attributes and user preferences. It uses the preference relation to represent the user preference information.
- **FL** is a fuzzy logic method that computes the general score by employing all the policy rules for describing the overall preferences of user requirements and by combining the policy influence parameters for each service.

We use the *mean absolute error* (MAE) to measure the selection accuracy [38]. MAE is a statistical accuracy metric computed by averaging absolute deviation of selections to the true data. For all active services and active users:

$$MAE = \frac{\sum_{u,s} | P_{u,s} - \widehat{P}_{u,s} |}{K}, \tag{27}$$

where $P_{u,s}$ denotes the actual standardized QoS value of service s consumed by user u, $\widehat{P}_{u,s}$ denotes the selected standardized QoS value by model, and K is the number of QoS attributes. A smaller MAE indicates better selection accuracy.

V.B. Service Selection Evaluation

As per the method presented in Section IV.B, we calculated cognitive levels of 100 users ranging from complete novice to expect, and obtain the threshold of users' cognitive levels for the target service type, $L_{threshold} = 0.45$. The users are

[1]http://www.uoguelph.ca/~qmahmoud/qws/

[2]Http://www.cnidp.cn

TABLE V
SELECTION PERFORMANCE COMPARISON

Methods	LowCognition			MediumCognition			HighCognition		
	#users 10	#users 20	#users 30	#users 10	#users 20	#users 30	#users 10	#users 20	#users 30
AW	0.371	0.370	0.368	0.288	0.285	0.281	0.238	0.235	0.238
FR	0.357	0.356	0.355	0.277	0.271	0.272	0.239	0.232	0.237
FL	0.345	0.345	0.343	0.279	0.272	0.268	0.229	0.226	0.224
Our Method	**0.255**	**0.242**	**0.231**	**0.238**	**0.227**	**0.213**	**0.215**	**0.209**	**0.202**

divided into three groups in terms of their respective cognitive levels and the threshold: *LowCognition* (below the threshold), *HighCognition* (above the threshold), and *MediumCognition* (equal to the threshold). We varied the number of the historical users (#*users*) between 10 and 30, and named the experiment results by the number of users, e.g., #*users* 10. The QoS preference records of the three cognitive levels of active users are used to study the selection accuracy. In this experiment, we set $\rho_1 = 5$, $\rho_2 = 3$, $\alpha = 0.5$. And the impact of ρ_1, ρ_2, and α on service selection performance will be discussed in Section V.D.

Table V shows the MAE-based service selection performance of the methods under evaluation for *LowCognition*, *HighCognition*, and *MediumCognition* users. Our method significantly improved the selection accuracy and consistently outperformed the others, especially for *LowCognition* users. Moreover, the performance of AW, FR, FL, and our method was significantly improved for the users with higher cognitive levels.

The causes affecting the selection performance of the AW, FR, and FL methods are as follows. The original idea of the AW method is to strictly follow the user-provided preferences (i.e., AUP) for service selection. The effectiveness of the AW method relies on the accuracy of the user-provided preference weights. It is inappropriate to apply the idea in our context because *LowCognition* users are unable to accurately formulate QoS preferences.

Similarly, the FR method is unsuitable for general users who do not usually possess a precise or sufficient level of knowledge and are not able to give the pairwise comparison weights on the numerous service candidates. The FL method's selection result depends on the matching rate of the policy rules: *high*, *middle*, or *low*. A service could be ranked the first only because it has a better matching with the *middle* policy rules. Moreover, we note that a unified policy cannot accurately reflect the great diversity of user preferences. The selection result may be quite different from user-preferred services once the policy does not match the user preferences.

Compared with the AW, FR, and FL, our method consistently provided a stable and reliable selection of services for the users with low cognitive levels because it could adjust the weights of user preferences.

V.C. Impact of Cognitive Level and #users

The impact of cognitive level on selection accuracy was investigated by varying the cognitive level of users from 0.1 to 0.9 with a step factor of 0.1 and by setting #*users* to 10. Fig. 3a shows the experiment results. Increasing the cognitive level resulted in performance improvements of AW, FL, and our method, i.e., better service selection was achieved for users with a higher cognitive level. In addition, our method is less sensitive to the cognitive level compared with the AW and FL method, because it could adjust the user preferences for service selection based on the cognitive level of all users for the target service type. Finally, our method consistently outperformed the others for users with varying cognitive levels.

The impact of #*users* on the selection accuracy was investigated by employing the users with *LowCognition* and by varying #*users* from 10 to 50 with a step factor of 10. This test is used to analyze inter-group significance, and the results indicate significant differences in service selection accuracy between different #*users* (p<0.05), as shown in Fig. 3b. The service selection performance of our method greatly improved with the increase of #*users*, whereas AW and FL (which do not exploit historical user data) were almost insensitive to #*users*. The results for users with *MediumCogtnition* and *HighCognition* also follow a similar pattern, because the PUP is extracted based on the corresponding preference data correlated with all users' cognitive levels, rather than the cognitive level of the target user only. Finally, the PUP weights become more accurate with the increasing #*users*.

V.D. Impact of ρ_1, ρ_2, and α

As discussed in Section IV.C and IV.D, there are three parameters that are key to the MAE-based performance of the proposed service selection model: ρ_1, ρ_2, and α. The two adjustment coefficients, ρ_1 and ρ_2 (introduced in Section IV.C) play an important role in determining the AUP weights. Preference coefficient α (introduced in Section IV.D) determines the contribution of AUP weights to the final selection result.

The impact of adjustment coefficient ρ_1 on service selection performance was investigated by varying the coefficient from 0 to 15 with a step factor of 1, and set #*users* to 10. We employed the users with *HighCognition* for the investigation. Fig. 4a shows the relation between ρ_1 and the MAE-based service selection performance when the preference coefficient α was 0.3, 0.5, 0.8, or 1.

Similarly, the impact of adjustment coefficient ρ_2 on service selection performance was investigated by varying the coefficient from 0 to 15 with a step factor of 1, and set #*users* to 10. This investigation employed the users with *LowCognition*. Fig. 4b shows the relation between ρ_2 and the service selection performance when the preference coefficient α was 0.3, 0.5, 0.8, or 1.

Fig. 4a(4b) shows that the service selection performance initially increases and then decreases with the increase of

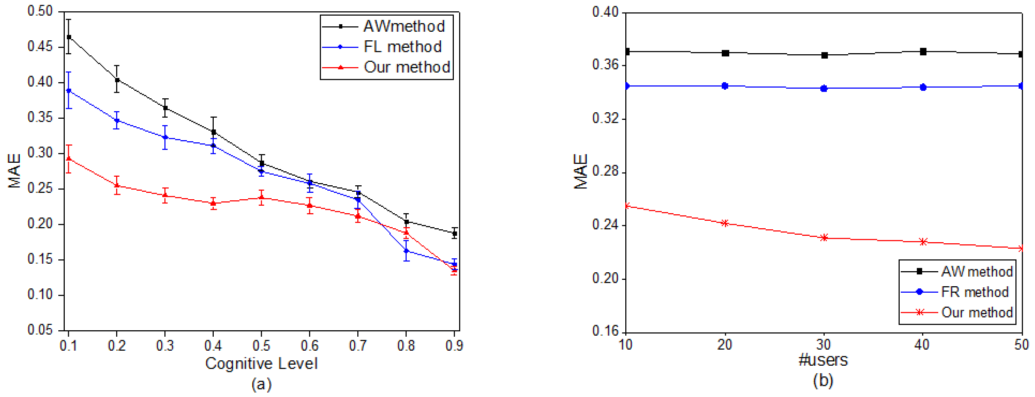

Fig. 3. Impact of the cognitive level and the number of historical users (#users) on selection performance (MAE). (a) Impact of the cognitive level of users. (b) Impact of the number of historical users (#users).

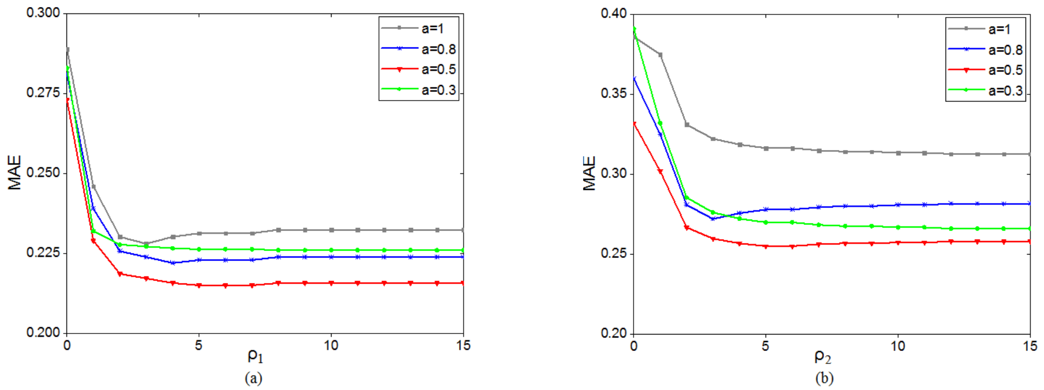

Fig. 4. Impact of α , ρ_1 , and ρ_2 on selection performance (MAE). (a) α Impact with changing ρ_1 . (b) α Impact with changing ρ_2 .

$\rho_1(\rho_2)$. With a very large value of ρ_1, selection accuracy maintains a steady value, because the AUP weights are always adjusted between the medium and the upper boundary as shown in Fig. 2 in Section IV.C. It indicates that the proposed service selection method is limited in a rational scope, and when $\rho_1 = 5$, and $\rho_2 = 3$, we get the minimum of MAE, i.e., the best performance of service selection for web services in the experiment setup. In a real service selection system, the optimal valued of $\rho_1(\rho_2)$ can be achieved via an arbitrary initial large value. The figures also show that, with the increase of α, the AUP make a greater contribution to the service selection result. The method cannot achieve an optimal selection result when α is too high or too low. Moreover, the figures show that when $\alpha = 1$, the selection result entirely depends on AUP, and the service selection performance is significantly decreased, which further validates the importance of PUP. In practice, the value of α is decided per the importance of AUP in the selection policy of the service selection system.

IV.E. Summary and Discussions

We have validated the importance of both AUP and OUP by experiments. Our experimental evaluation results show that our model outperforms previous models [5], [11], [37], [6], [12]. We have investigated the performance impact of all key parameters in our model to validate its universality. The experiments helped us obtain deeper insights on the proposed service selection approach.

Importance of user preferences: Our experiments validated the importance of considering the characteristics of user preferences (as stated in [1], [2], [3]). As shown in Figs. 3 and 4, user satisfaction greatly improves with consideration of AUP and PUP. Since PUP is often overlooked in previous models, we investigated further the impact of PUP on service selection performance. As Fig.4 shows, when PUP was ignored, the performance was significantly decreased. The above results indicate that, with AUP and PUP considered together, the service selection model can result in a higher user satisfaction.

Selection accuracy of our model: Compared with the previous models, our model significantly improves the selection accuracy, as showed in Table V and Fig. 3. It is because our model considers both the AUP and PUP, and can adjust user-provided service selection preferences by adjusting the AUP weights and by supplementing the PUP weights. By exploiting historical user data, our model delivers better service selection results when the number of historical users increases, as showed in Fig. 3b.

Universality of our model: Inexperienced service users are not the focus of previous QoS-based service selection models [4], [7], [10], [17], [20], [43], [45]. However, in practice, service users include inexperienced users, slightly experienced users, and highly experienced users. A good service selection model should perform well for all these kinds of users. Table V and Fig. 3a show that our model outperforms others consistently for users with varying cognitive levels.

VI. Conclusion

This paper proposes a novel service selection approach such that satisfactory services could be recommended for all kinds of users, even the ones with limited service usage experiences and low service cognitive levels. In view of the user preference data fuzziness and inaccuracy, the proposed approach supports a user-friendly means of flexibly expressing QoS preferences and measuring the reliability of user preferences per all users' service experience and cognitive levels. The approach employs a user preference quantification phase to fuzzify AUP, and a two-step process to adjust the AUP weights and supplement the PUP weights. The preference adjustment method can be exploited by other service discovery, selection, and composition models that employ user preferences.

The experimental evaluations were conducted via real datasets. The evaluation results show that the proposed cognitive-level-based adjustment of user preferences is necessary and effective for users with varying service experience, and yields more accurate and reliable service selection models.

To gather the real service selection and usage data we need, our future work includes setting up our own Internet-based service sharing platform[3], and collecting more data about user preferences and usage records. The new platform would facilitate public use of the proposed service selection model and our enhancement to the model via real datasets.

ACKNOWLEDGMENT

This work was supported in part by the National Science Foundation of China (Grant No. 61472047). Shangguang Wang is the corresponding author.

References

[1] D. Mobedpour and C. Ding, "User-centered design of a QoS-based web service selection system," *Service Oriented Computing and Applications*, vol. 7, no. 2, pp. 117-127, Jun. 2013.

[2] M. Almulla, K. Almatori, and H. Yahyaoui, "A qos-based fuzzy model for ranking real world web services," in *Proc. IEEE Int. Conf. Web Serv.*, pp. 203-210,2011.

[3] H.-C. Wang, C.-S. Lee, and T.-H. Ho, "Combining subjective and objective QoS factors for personalized web service selection," *Expert Systems with Applications*, vol. 32, no. 2, pp. 571-584, Feb. 2007.

[4] G. Kang, J. Liu, M. Tang, X. Liu, B. Cao, and Y. Xu, "AWSR: Active web service recommendation based on usage history," in *Proc. IEEE Int. Conf. Web Serv.*, pp. 186-193, 2012.

[5] M. Alrifai, T. Risse, and W. Nejdl, "A hybrid approach for efficient Web service composition with end-to-end QoS constraints," *ACM. Trans. Web*, vol. 6, no. 2, pp. 7, May.2012.

[6] L. Zhao, Y. Ren, M. Li, and K. Sakurai, "Flexible service selection with user-specific QoS support in service-oriented architecture," *J. Network and Computer Applications*, vol. 35, no. 3, pp. 962-973, May. 2012.

[7] L. Zeng, B. Benatallah, A. H. Ngu, M. Dumas, J. Kalagnanam, and H. Chang, "Qos-aware middleware for web services composition," *IEEE. Trans. Software Engineering*, vol. 30, no. 5, pp. 311-327, May.2004.

[8] J. Li, W. Su, and M. Chen, "Web Services Discovery Model Based on QoS and User Preference," *Modern Computer*, vol. 4, no. 1, pp. 49-52, Apr. 2010.

[9] Y. Liu, A. H. Ngu, and L. Z. Zeng, "QoS computation and policing in dynamic web service selection," in *Proc. 13th Int. WWW Conf. Alternate track papers & posters*, pp. 66-73, 2004.

[10] L. Shao, J. Zhang, Y. Wei, J. Zhao, B. Xie, and H. Mei, "Personalized qos prediction forweb services via collaborative filtering," in *Proc. IEEE Int. Conf. Web Serv.*, pp. 439-446, 2007.

[11] R. Berbner, M. Spahn, N. Repp, O. Heckmann, and R. Steinmetz, "Heuristics for qos-aware web service composition," in *Proc. IEEE Int'l Conf. Web Serv.*, pp. 72-82, 2006.

[12] Z. Wu, and M. Yuan, "User-preference-based service selection using fuzzy logic," in *Proc. Int. Conf. Network and Service Management*, pp. 342-345, 2010.

[13] S. Lamparter, A. Ankolekar, R. Studer, and S. Grimm, "Preference-based selection of highly configurable web services," in *Proc. 16th Int. Conf. Word Wild Web*, pp. 1013-1022, 2007.

[14] I. V. Papaioannou, D. T. Tsesmetzis, I. G. Roussaki, and M. E. Anagnostou, "A QoS ontology language for web-services," in *Proc. 20th Int. Conf. Advanced Information Networking and Applications*, pp. 101-106, 2006.

[15] V. X. Tran, H. Tsuji, and R. Masuda, "A new QoS ontology and its QoS-based ranking algorithm for Web services," *Simulation Modeling Practice and Theory*, vol. 17, no. 8, pp. 1378-1398, Jun. 2009.

[16] A.R. Corte´s, O. Martı´n-Dı´az, A.D. Toro, and M. Toro, "Improving the automatic procurement of web services using constraint programming," *J. Cooperative Information Systems*, vol. 14, no. 04, pp. 439-467, Dec. 2005.

[17] D. Mobedpour, C. Ding, and C.-H. Chi, "A qos query language for user-centric web service selection," in *Proc. IEEE Int. Conf. Serv. Comput.*, pp. 273-280, 2010.

[18] Z. Xu, "A procedure for decision making based on incomplete fuzzy preference relation," *Fuzzy optimization and decision making*, vol. 4, no. 3, pp. 175-189, Jul. 2005.

[19] J. T. Garcı, M. Del Moral, M. Martínez, and E. Herrera-Viedma, "A consensus model for group decision making problems with linguistic interval fuzzy preference relations," *Expert Systems with Applications*, vol. 39, no. 11, pp. 10022-10030, Sep. 2012.

[20] J.-Q. Wang, and H.-Y. Zhang, "Multicriteria decision-making approach based on Atanassov's intuitionistic fuzzy sets with incomplete certain information on weights," *IEEE. Trans. Fuzzy Systems*, vol. 21, no. 3, pp. 510-515, Jun.2013.

[21] F.-G. Liu, F. Xiao, and Y.-D. Lin, "Combining experts' opinion with consumers' preference in web service QoS selection," in *Proc. Int. Conf. Machine Learning and Cybernetics*, pp. 1740-1746, 2013.

[22] I. R. Assembly, *Methodology for the subjective assessment of the quality of television picture*s, International Telecommunication Union, 2003.

[23] J. S. Uebersax, "Likert scales: dispelling the confusion," S*tatistical methods for rater agreement*, vol. 31, no. 1, available at http://john-uebersax.com/stat/likert.htm, Aug. 2006.

[24] Z.-P. Fan, J. Ma, and Q. Zhang, "An approach to multiple attribute decision making based on fuzzy preference information on

[3]http://qoecenter.com/

alternatives," *Fuzzy sets and systems*, vol. 131, no. 1, pp. 101-106, 2002.

[25] P. Wang, K.-M. Chao, C.-C. Lo, C.-L. Huang, and Y. Li, "A fuzzy model for selection of QoS-aware web services," in *Proc. IEEE Int. Conf. e-Business Engineering*, vol. 1, pp. 585-593, 2006.

[26] V. X. Tran, and H. Tsuji, "QoS based ranking for web services: Fuzzy approaches," in *Pro. 4th Int. Conf. Next Generation Web Serv. Practices*, pp. 77-82, 2008.

[27] H.-K. Chiou, and G.-H. Tzeng, "Fuzzy multiple-criteria decision-making approach for industrial green engineering," *Environmental Management*, vol. 30, no. 6, pp. 0816-0830, Dec. 2002.

[28] J. L. Yang, H. N. Chiu, G.-H. Tzeng, and R. H. Yeh, "Vendor selection by integrated fuzzy MCDM techniques with independent and interdependent relationships," *Information Sciences*, vol. 178, no. 21, pp. 4166-4183, Nov. 2008.

[29] D. McGonigle, and K. Mastrian, "Introduction to information, information science, and information systems," *Nursing informatics and the foundation of knowledge*, vol. 2, no. 1, pp. 18-31, 2012.

[30] F. I. Craik, "Levels of processing: Past, present... and future?," *Memory*, vol. 10, no. 5, pp. 305-318, Sep. 2002.

[31] N. Otsu, "A threshold selection method from gray-level histograms," *Automatica*, vol. 11, no. 285-296, pp. 23-27, 1975.

[32] N. Otsu, "An automatic threshold selection method based on discriminate and least squares criteria," *Denshi Tsushin GakkaiRonbunshi*, vol. 63, pp. 349-356, Jan. 1979.

[33] N. Zhong, and A. Skowron, "A rough set-based knowledge discovery process," *Applied mathematics and computer science*, vol. 11, no. 3, pp. 603-620, Sep.2001.

[34] M. Li, B. Yu, O. Rana, and Z. Wang, "Grid service discovery with rough sets," *IEEE Trans. Knowledge and Data Engineering*, vol. 20, no. 6, pp. 851-862, Aug.2008.

[35] M. Ortega, Y. Rui, K. Chakrabarti, S. Mehrotra, and T. S. Huang, "Supporting similarity queries in MARS," in *Proc. 5th ACM Int. Conf. Multimedia*, pp. 403-413, 1997.

[36] L.-S. Shao, L. Zhou, J.-F. Zhao, B. Xie, and H. Mei, "Web service QoS prediction approach," *J. Software*, vol. 20, no. 8, pp. 2062-2073, Aug.2009.

[37] J. E. Haddad, M. Manouvrier, G. Ramirez, and M. Rukoz, "QoS-driven selection of web services for transactional composition," in *Proc. IEEE Int. conf. Web Serv.*, pp. 653-660, 2008.

[38] Z. Zheng, H. Ma, M. R. Lyu, and I. King, "Qos-aware web service recommendation by collaborative filtering," *IEEE Trans. Serv. Comput.*, vol. 4, no. 2, pp. 140-152, Apr.2011.

[39] X. Chen, Z. Zheng, X. Liu, Z. Huang, and H. Sun, "Personalized qos-aware web service recommendation and visualization," *IEEE Trans. Serv. Comput.*, vol. 6, no. 1, pp. 35-47, Jan. 2013.

[40] X. Zhao, Z. Wen, and X. Li, "QoS-aware web service selection with negative selection algorithm," *Knowledge and information systems*, vol. 40, no. 2, pp. 349-373, Aug. 2014.

[41] E. Al-Masri, Q. H. Mahmoud, "*Discovering the best web service*," in *Proc. 16th Int. Conf. Word Wild Web,* pp. 1257-1258, 2007.

[42] E. Al-Masri, Q. H. Mahmoud, "Qos-based discovery and ranking of web services," in *Proc. 16th Int. Conf. Computer Communication & Networks,* pp.529-534, 2007.

[43] X. Zhao, L. Shen, X. Peng, and W. zhao, "Toward SLA-constrained service composition: An approach based on a fuzzy linguistic preference model and an evolutionary algorithm," *Information Sciences*, vol. 316, no. 1, pp. 370-396, 2015.

[44] E. Khanfir, C. El Hog, R. Ben Djmeaa, B. Amor, and I. Amous, "A web service selection framework based on user's context and QoS," in *Proc. IEEE Int. Conf. Web Serv.*, pp. 708-711, 2014.

[45] V. P. Modekurthy, K. K. Fletcher, and X. Liu, "Personal Preference and Trade-off based Additive Manufacturing Web Service Selection," in *Proc. IEEE Int. Conf. Web Serv.*, pp.440-447, 2015.

[46] X. Liu, K.K. Fletcher, and M. Tang, "Service Selection based on Personalized preference and trade-offs among QoS factors and price," in *Proc. IEEE. 1st Int. Conf. Serv. Economics*, 2012.

[47] K.K. Fletcher, X. F. Liu, and M. Tang, "Elastic personalized non functional attribute preference and trade-off based service selection," *ACM Trans. Web*, vol. 9, no. 1 pp. 1-27, 2015.

[48] K. K. Fletcher, X. F. Liu, and M. X. Cheng, "Aggregating ranked services for selection," in *Proc. IEEE Int. Conf. Serv. Comput.*, 2014.

[49] L.A. Zadeh, "The role of fuzzy logic in the management of uncertainty in expert systems," *Fuzzy sets and systems*, 1983, vol. 11, no. 1, pp. 199-227, 1983.

[50] L.A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning—I," *Information sciences*, vol.8, no. 3, pp. 199-249, 1975.

Lingyan Zhang received the BS degree in network engineering from Beijing University of Posts and Telecommunications in 2009. She is currently working toward the PhD degree in the State Key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunications, China. Her research interests include service computing, cloud computing, quality of experience and data mining.

Shangguang Wang is an Associate Professor at the State Key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunications (BUPT). He received his Ph.D. degree at BUPT in 2011. He has co-authored more than 100 papers. He has played a key role at many international conferences such as General Chair and PC Chair. His research interests include Service Computing, Cloud Computing, and Edge Computing. He is a Senior Member of the IEEE.

Raymond K.Wong is currently an Associate Professor at the School of Computer Science & Engineering, University of New South Wales, Sydney, Australia. From 2005-2011, he founded and led the Database Research Group at National ICT Australia (NICTA). He was also in the founding team of several startup companies. He has published more than 150 research publications and 2 patents in the areas related to databases, data mining and Web technologies. He has supervised 13 PhD, 10 masters and 60 honours students to completion. He received his BSc from Australian National University, and MPhil and PhD from Hong Kong University of Science & Technology.

Fangchun Yang received his Ph.D.in communications and electronic systems from the Beijing University of Posts and Telecommunication in 1990. He is currently professor at the Beijing University of Posts and Telecommunication, China. He has published six books and more than 80 papers. His current research interests include network intelligence, service computing, communications software, soft-switching technology, and network security. He is a fellow of the IET.

Rong Chang received his PhD degree in computer science and engineering from the University of Michigan in 1990. He is with IBM T.J. Waston Research Center leading a global team advancing IoT cloud services technologies. He holds 30+ patents and has published 40+ papers. He is Member of IBM Academy of Technology, ACM Distinguished Engineer, Chair of IEEE-CSTechnical Committee on Services Computing, and Associate Editor-in-Chief of IEEE Trans. on Services Computing.